Literature Review of AI Music Recommendation

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ABSTRACT

This project focuses on developing an AI-powered music recommendation system by harnessing diverse music-related data sources and employing various machine learning techniques. The process involves data acquisition, cleaning, feature extraction, and model construction, with a focus on improving recommendation accuracy. The system's performance is evaluated using metrics like MAE and RMSE, and it is integrated into a user-friendly platform with continuous feedback and stringent data privacy measures. The objective is to create an efficient and secure music recommendation system that enhances user music discovery.

KEYWORDS

Machine Learning, Data Collection, Music Recommendation System, Evaluation Metrics, Matrix Factorization, Music Discovery

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1 INTRODUCTION

The realm of music consumption and discovery has been dramatically transformed in recent years, owing to the advent of digital streaming platforms and the proliferation of music databases. Amid this evolving landscape, the application of Artificial Intelligence to music recommendation systems has emerged as a pivotal endeavor, with the promise of enhancing user experiences and facilitating the exploration of a vast and diverse musical repertoire. This literature review embarks on an exploration of the journey to develop an AI-driven music recommendation system, a journey marked by data gathering, preprocessing, feature engineering, model construction, evaluation, and user-centric considerations. [1] [5]

The fundamental goal of this endeavor is to create a music recommendation system harnessing the capabilities of AI. The assembly of an extensive dataset encompassing diverse music-related information, spanning songs, artists, user preferences, playlists, and user interactions. These interactions, including user likes, skips, and ratings, are pivotal to user engagement and musical preferences. Noteworthy data sources include established streaming platforms, such as Spotify and Last.fm, and user-contributed datasets like the Million Song Dataset, each contributing valuable insights into the music landscape.

Intertwined with data collection is the task of data preprocessing. These are intertwined by using multiple datasets, comparing each other, and displaying songs and recommendations; This phase entails addressing missing values, removing duplicates, and ensuring data consistency, rendering the dataset amenable to AI-driven analysis. The transformation of raw data into a format suitable for machine learning is an essential step in the process, with numerical representations and embeddings being employed to encode both songs and users effectively.

The efficacy of the music recommendation system hinges on extracting relevant features from the dataset, illuminating the intricate nuances of songs and users alike. Features of interest encompassing genres, tempo, artist popularity, user listening history, and more. The subsequent construction of the recommendation model involves a multifaceted approach, drawing upon various techniques such as collaborative filtering, content-based filtering, matrix factorization, and deep learning. These techniques collectively strive to discern intricate patterns within the music data, enabling the system to provide personalized recommendations.

Central to the model's refinement and optimization is using historical user interactions with songs as the basis for training. To gauge the model's effectiveness and predictive power, the dataset is randomly partitioned into training, validation, and test sets, with performance evaluation carried out using Mean Absolute Error(MAE), Root Mean Squared Error (RMSE), and precision-recall metrics.

This comprehensive literature review thus embarks on a journey through the multifaceted terrain of AI-driven music recommendation systems, providing insights into the methodologies, challenges, and ethical considerations that underpin the development of a system designed to enhance the musical journeys of users while safeguarding their data and privacy.

2 DATASET

This section introduces the different types of datasets used in the research. The choice of dataset depends on your specific project goals, data availability, and the type of music recommendation system you intend to build. It's common to combine multiple datasets to create a more comprehensive and accurate model.

2.1 Spotify

The Spotify dataset is a comprehensive resource for music-related research, offering data on songs, artists, user preferences, playlists, and interactions.[6] It is valuable for developing music recommendation systems, genre classification, artist popularity analysis, and user engagement studies. Leveraging this dataset enhances our

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understanding of music consumption trends and user behavior, driving innovation in music services and experiences. [8]

2.2 Apple Music

The Apple Music dataset comprises a diverse array of music-related information, including songs, artists, playlists, and user interactions. This dataset offers valuable insights for research, enabling the development of advanced music recommendation systems and enhancing the understanding of user preferences. Apple Music's dataset is a vital resource in music analytics, contributing to the evolution of music services and personalized music discovery.[2]

3 METHODS

The choice of method depends on the specific goals of your music recommendation system and the nature of the available data. Often, a combination of specific methods is employed to achieve the best results, providing users with personalized and diverse music recommendations.

3.1 Collaborative Filtering

Collaborative filtering is a widely used method that recommends items (in this case, music) based on the preferences and behavior of similar users. It can be user-based or item-based, relying on user-item interaction data to make recommendations. [7]

3.2 Content Based Filtering

Content-based filtering recommends music based on the content attributes of songs and the user's historical preferences. It focuses on matching user profiles with music features like genre, tempo, and lyrics. [4]

3.3 Matrix Factorization

Matrix factorization techniques, such as Singular Value Decomposition (SVD) and Alternating Least Squares (ALS), are used to factorize user-item interaction matrices to discover latent factors influencing recommendations. [3]

3.4 Deep Learning

Deep learning methods are all neural networks. Deep learning is just using a neural network with several layers. These include deep recommendation models, which are used to model complex patterns in user behavior and music features for more accurate recommendations. [1]

4 EXTRA GOALS

Upon achieving satisfactory performance, the recommendation algorithm is seamlessly incorporated into a user-friendly platform, complete with an intuitive interface. This interface becomes the conduit through which users interact with the system, fostering an engaging and efficient music discovery experience. Moreover, provisions are made for feedback collection, ensuring continuous improvement and adaptability to evolving user preferences.

Crucially, the ethical dimensions of user data handling and privacy concerns are addressed with utmost diligence. Stringent measures are implemented to safeguard user data, affirming a commitment to data security and user privacy throughout the system's life cycle.

5 CONCLUSION

This literature review discussed the dynamic and multifaceted nature of music recommendation systems. It represents an opportunity to shape the future of music discovery, providing users with personalized and engaging experiences. As music streaming platforms and user expectations evolve, this endeavor remains vital in enhancing the intersection of AI and music, offering a road map for ongoing innovation and refinement in music recommendation. I first explained the information of what is going to be done starting with the introduction. Second, I explained the specific datasets that will be used. This

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